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Original Article

Multi-Signal ERP Graphs for Predictive & Prescriptive Supply Chain Resilience

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***Abstract** - Modern supply-chain networks are becoming more susceptible to disruptions due to geopolitical shifts, changing demand, and pressures related to ESG compliance. Although Enterprise Resource Planning (ERP) systems provide transactional visibility, they fall short in offering substantial predictive capabilities, and independent AI modules typically fail to enable prescriptive decision-making. This study introduces a Multi-Signal ERP Graph (MSEG) framework that merges various enterprise, IoT, and ESG data into a unified graph model to facilitate predictive risk assessment and provide prescriptive strategies for resilience. By utilizing a hybrid Graph Neural Network (GNN) along with a constrained optimization model, MSEG evaluates the probability of disruptions and recommends mitigation strategies while taking into account cost and sustainability constraints. Simulation experiments carried out on synthetic supply chains consisting of 300 nodes demonstrate an average enhancement of 3.2 days in detection lead time, an increase of 8.6% in fill rates, and a 76% decrease in ESG violations compared to conventional ERP alerts. The proposed system improves both predictive and prescriptive analytics, leading to a more efficient decision-making process for resilient and sustainable supply chain management.*

***Keyword** - Supply-Chain Resilience; Enterprise Resource Planning (ERP); Graph Neural Networks; Multi-Signal Fusion; Prescriptive Analytics; Early-Warning Systems; ESG Compliance.*

1. Introduction

Global supply chains consist of complex and interconnected networks where a single disruption can impact suppliers, logistics providers, and retailers. Conventional ERP systems accumulate a large quantity of operational data but remain limited to deterministic planning and reactive responses. The absence of proactive intelligence leaves organizations vulnerable to cascading failures, such as semiconductor shortages or port shutdowns. Although artificial intelligence has enhanced forecasting accuracy, most methodologies still primarily focus on prediction, providing risk evaluations without actionable response plans. The next frontier lies in prescriptive analytics, where AI systems must recommend feasible and policy-compliant recovery actions.

This paper addresses three fundamental gaps:

1. Data Silo Gap - ERP, IoT, and ESG signals remain unintegrated, leading to partial visibility.
2. Analytical Gap - Predictive models lack topological awareness of inter-firm dependencies.
3. Decision Gap - Few systems translate analytics into executable mitigation strategies.

The proposed Multi-Signal ERP Graph (MSEG) framework addresses existing shortcomings by developing a dynamic graph representation of the enterprise network and incorporating signals from various sources to improve predictive and prescriptive intelligence. The organization of the paper is as follows: Section II reviews pertinent literature; Section III presents the mathematical formulation of the problem; Section IV explains the architecture of the MSEG system; Section V details the methodology and experiments performed; Section VI highlights the results; and Section VII concludes the paper.

2. Related Work

2.1. Predictive Analytics for Resilience

Machine learning techniques, including random forests and LSTMs, have been employed for predicting demand and assessing risk [1], [4]. Nevertheless, these methods consider each supplier separately, overlooking the effects of their interactions. Graph-based learning [3], [6] employs message passing to understand relationships between nodes, allowing for the modeling of risk transfer across different tiers.

2.2. Prescriptive Decision Frameworks

Prescriptive models employ optimization methods to recommend actions. Smyth [1] and Choi et al. [2] demonstrate that combining simulation with cost-based optimization improves decision-making quality. Nevertheless, these models rely on aggregated data and rarely integrate real-time information from ERP systems.

2.3. ESG and Sustainability Integration

Recent works [2], [9] embed environmental metrics into supply-chain optimization, aligning with the Triple Bottom Line concept:

$$U = f(P, N, E)\ U = f(P, N, E)\ U = f(P, N, E)$$

Where P = profit, N = social equity, and E = environmental impact. MSEG extends this by constraining prescriptive actions under ESG thresholds.

Despite advances in predictive modeling, prescriptive optimization, and ESG-aware planning, no existing framework unifies multi-signal ERP data, graph-based dependency modeling, and constrained prescriptive decision-making into a single system. This gap motivates the proposed MSEG framework

2.4. Digital Transformation and ERP Modernization

Studies [8], [15] highlight that cloud-based ERP systems enhance integration among various functions. When integrated with IoT and graph analytics, they create a technological basis for multi-signal fusion. Nonetheless, a fully realized predictive-plus-prescriptive system derived from ERP graphs remains largely unexplored. The MSEG framework aims to address this gap.

3. Problem Formulation

Let a supply-chain network be represented as a directed graph $G = (V, E)$ where nodes $v_i \in V$ denote firms and edges $e_{ij} \in E$ represent transactional or logistical links.

Each node carries a multi-signal feature vector: $X_i = [x_i^{ERP}, x_i^{IoT}, x_i^{EsG}, x_i^{Mkt}]$ and a temporal series $T_i(t)$ capturing dynamic behavior.

The objective is twofold:

1. Prediction: Estimate disruption probability $p_i(t)$ for each node.
2. Prescription: Select optimal mitigation actions $a_i(t)$ minimizing expected loss while satisfying constraints.

Mathematically:
$\min_{a_i} \sum_i C_i(a_i)$ s.t. $R_i(a_i) \leq R\_th$, $E_i(a_i) \geq E\_min$ (1)
where C_i = cost, R_i = residual risk, E_i = ESG compliance metric.
Equation (1) formalizes the prescriptive layer as a constrained optimization problem guided by predictive risk outputs.

4. System Architecture and Model

4.1. Overview

The MSEG system architecture comprises five sequential modules:

1. Data Ingestion Layer - integrates ERP transaction logs, IoT sensor feeds, and ESG databases.
2. Graph Constructor - transforms relational ERP entities into a knowledge graph.
3. Feature Fusion Engine - aligns multi-signal data temporally and semantically.
4. Predictive Module (ST-GNN) - computes node-level disruption probabilities.
5. Prescriptive Module - applies constrained optimization to recommend mitigation actions.

4.2. ERP Graph Construction

ERP entities, including suppliers, purchase orders, and inventory items are converted to graph nodes, while transactional dependencies form edges. Edge attributes include lead time L_{ij}, cost C_{ij}, and reliability q_{ij}. $A_{ij} = \{$ 1, if active transactional link exists; 0, otherwise $\}$ Resulting in adjacency matrix $A \in \{0,1\}^{nxn}$.

4.3. Multi-Signal Feature Fusion

For each node: $Z_i = f\_fusion(x_i^{ERP}, x_i^{IoT}, x_i^{EsG}, x_i^{Mkt})$
Where f_fusion concatenates normalized vectors and applies dimensionality reduction via PCA. Temporal alignment ensures synchronized input across PCA reduces fused embeddings to a 64-dimensional latent space.

4.4. Spatio-Temporal GNN Predictor

Each node embedding $h_i(t)$ evolves as: $h_i(t+1) = \sigma(\sum_j \in N(i)\ W_1\ h_j(t) + W_2\ X_i(t))$
Where W_1, W_2 are learnable weight matrices and σ is a ReLU activation. The final risk score: $R_i = \mathrm{softmax}(W_r\ h_i(T))$ (2) gives probability of disruption for node i.

4.5. Prescriptive Decision Module

Predicted risk outputs feed an optimization engine that recommends preventive or corrective actions a_i. The model minimizes combined cost–risk objective:

$$J = \sum_i (\lambda_1 R_i(a_i) + \lambda_2 C_i(a_i) - \lambda_3 E_i(a_i)) \quad (3)$$

Subject to logistical and ESG constraints. Lagrangian multipliers handle trade-offs between economic and environmental goals.

4.6. Dashboard & Scenario Evaluator

A front-end interface visualizes node-level risk, recommended actions, and expected KPI improvements. Color-coded maps indicate hotspots; charts display cost–benefit projections.

5. Methodology

5.1. Research Approach

A combined experimental and analytical method was utilized, merging simulated ERP-IoT data streams with real performance benchmarks recorded in current studies [1] [13]. The experiment took place in three stages:

1. Data Generation & Integration: A comprehensive dataset comprising 50 GB of simulated ERP transaction and the simulated data volume corresponding to approximately six months of transactional activity, IoT sensor data, and ESG compliance records was produced to represent a supply chain network of 300 nodes.
2. Model Development: A spatio-temporal graph neural network (GNN) was trained using 70% of the dataset, with 15% set aside for validation and the remaining 15% for testing.
3. Decision-Making Optimization: Monte Carlo simulations were employed to produce potential actions (such as rerouting, capacity reallocation, and source substitution), which were then optimized under ESG and cost constraints through a mixed-integer linear programming (MILP) solver.

Performance metrics were compared with baseline ERP heuristics to measure gains in early-warning accuracy and operational efficiency.

5.2. Evaluation Metrics

Three core Key Performance Indicators (KPIs) were defined:

1. Detection Lead Time (DLT) Time difference between model prediction and actual disruption detection.
2. Fill-Rate Improvement (FRI) Percentage increase in order-fulfilment rate compared to baseline ERP scheduling.
3. Compliance Violations (CV) Number of recommended actions breaching ESG or contractual limits.

These were calculated using formulas summarized in Table 5.1

Table 1: Metric Definitions

Metric	Formula	Description
DLT	$t_{pre}d - t_{o\beta s}$	Average days of advance warning
FRI	(FR_MSEG − FR_base) / FR_base × 100	Relative fill-rate gain
CV	$\sum 1_{(ai \notin \Omega^{EsG})}$	Count of ESG-violating actions

5.3. Simulation Configuration

Table II lists the primary parameters used in the simulation environment.

Table 2: Simulation Parameters

Parameter	Symbol	Value	Description
Number of nodes	nnn	300	Enterprises in network
Average degree	kkk	4.5	Mean inter-firm links
Time window	TTT	180 days	Forecast horizon
Disruption probability	p_dp	0.1 – 0.3	Event frequency
Learning rate	η	0.001	GNN training step size
ESG threshold	τ_ESG	0.8	Minimum compliance score

6. Results And Discussion

6.1. Predictive Performance

In 500 Monte-Carlo simulations, MSEG yielded an average DLT of 4.8 days (± 0.6), whereas the baseline ERP system only measured 1.6 days. The ROC-AUC value for classifying disruptions was 0.91, indicating a high level of predictive accuracy.

6.2. Prescriptive Optimization Results

Table 3: Performance Summary

Metric	Baseline	MSEG	Metric
Detection Lead Time (days)	1.6	4.8	Detection Lead Time (days)
Fill-Rate (%)	78.4	87.0	Fill-Rate (%)
Compliance Violations (count)	3.4	0.8	Compliance Violations (count)

Observation: Prescriptive actions generated by MSEG reduced expected financial losses by 12 % while keeping carbon intensity below baseline values.

6.3. Sensitivity Analysis

Regression of productivity gain against strategic variables yielded $P = 0.15 + 0.47D + 0.29I + 0.31S + \varepsilon$ with $R^2 = 0.83$. Digital adoption (DDD) was the strongest predictor, confirming the importance of IoT and real-time data where D denotes digital integration, inventory flexibility, and S supplier diversity.

6.4. Engineering Implications

1. System Scalability: By implementing graph partitioning and leveraging parallel GPU training, it achieves demonstrates scalable behavior in simulated environments exceeding 10,000 nodes
2. Integration with Existing ERP: The framework operates through an API layer, facilitating integration without the need to alter the core modules.
3. Computation Cost: The average processing time is around 3.7 seconds for 300 nodes on an RTX 4090 GPU.
4. Model Explainability: The attention weights within the GNN emphasize significant supply-chain connections, providing clear insights for early warnings.

6.5. Case Study Validation

1. Semiconductor Shortage Replay: MSEG predicted Tier-2 supplier disruption 5 days in advance, enabling inventory realignment and saving ≈ $1.2 M in backorder costs.
2. Logistics Port Closure: Model recommended multi-route allocation; fill-rate sustained at 92 % versus 78 % baseline.
3. ESG Violation Scenario: Prescriptive module rejected low-cost actions exceeding emission thresholds, demonstrating ethical constraint handling.

6.6. Discussion

The results validate the hypothesis that strategic multi-signal integration enhances resilience beyond traditional ERP analytics. Key insights include:

- Graph-based Context: Captures multi-tier dependencies often missed in tabular analysis.
- Hybrid Predictive–Prescriptive Link: Transforms probabilistic risk estimates into quantifiable actions.
- ESG-Aligned Optimization: Maintains sustainability goals while improving efficiency.
- Real-Time Adaptivity: Re-trains continuously with new ERP transactions, supporting dynamic supply networks.

7. Conclusion And Future Scope

This research presents the Multi-Signal ERP Graph (MSEG) framework, designed to improve both predictive and prescriptive resilience in supply chain operations. By integrating ERP, IoT, and ESG signals into a graph-learning model, this framework offers a comprehensive view of inter-firm dependencies along with robust decision-making support. Simulation results demonstrate significant enhancements in lead-time detection, fill rates, and compliance performance when compared to conventional systems. MSEG exemplifies how AI-driven graph analytics can transform ERP systems from simple transactional databases into platforms that support strategic findings demonstrating how ERP-centered AI systems can support national-scale resilience across regulated and mission-critical supply networks.

Future extensions include:

- Incorporating real transaction streams for online learning.
- Extending optimization to multi-objective reinforcement learning.
- Integrating natural-language interfaces for executive decision queries.
- Validating framework across live industrial ERP ecosystems.

The findings indicate that synergizing AI, optimization, and sustainability principles can redefine enterprise resilience in the Industry 5.0 era.

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